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Does Context Matter for the Relationship between Deprivation and All-Cause Mortality? The West vs. the Rest of Scotland

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Abstract

One of the assumptions that is often made in modeling the relationship between deprivation and mortality is that this relationship will remain the same across space. There is little justification presented in the literature as to why the deprivation-mortality relationship will be homogenous across space. The homogeneity of this relationship over space is an empirical question and most of the published literature does not formally test this relationship. Using postcode data for Scotland (UK), this study addresses this research gap and tests the hypothesis of spatial heterogeneity in the relationship between area-level deprivation and mortality. Research into health inequalities frequently fails to recognise spatial heterogeneity in the deprivation-health relationship, assuming that global relationships apply uniformly across geographical areas. In this study, exploratory spatial data analysis methods are used to assess local patterns in deprivation and mortality. A variety of spatial regression models are then implemented to examine the relationship between deprivation and mortality. The hypothesis of spatial heterogeneity in the relationship between deprivation and mortality is rejected. Implications of the homogeneity of the deprivation-mortality relationships for addressing health inequities are discussed in light of the inverse care law.

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Keywords

Deprivation; Mortality; Health Inequalities; Scotland; Health Policy; Postcode areas; Small-area analysis; Spatial analysis; Spatial heterogeneity

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Introduction

The last decade witnessed a surge in epidemiologic research emphasizing the context-sensitive nature of the relationship between health outcomes and their determinants. That context matters might seem obvious but has often been neglected in traditional study designs. Traditionally, studies have often modeled health outcomes as a function of individual characteristics, assuming that individuals' behavior and health outcomes are independent of other individuals and of neighborhood or regional characteristics (Diex-Roux, 1998). A research focus on multi-level modeling (Schulz et al., 2005), neighborhood effects (Pickett and Pearl, 2000) and built environment (Mobley et al., 2006; Northridge, Sclar & Biswas, 2003) begins to address this gap. This body of research focuses on factors such as the interaction between individual level and area-level determinants of health outcomes, on the mediating effect of social interactions and on how urban form is related to health outcomes such as obesity. Although these contextual factors are often implicitly spatial, an explicit focus on spatial heterogeneity is still rare (see Mobley et al., 2008a and 2008b for exceptions). The goal of this study is to explore the role of spatial heterogeneity in the relationship between deprivation and mortality.

Homogeneity and Heterogeneity in the Deprivation - Mortality Relationship

The relationship between area-level measures of deprivation and all-cause mortality has been extensively researched (Hanlon et al., 2001; Hanlon et al., 2005; Registrar General for Scotland, 2007; Griffiths and Fitzpatrick, 2001; Carstairs and Morris, 1989; Walsh et al., 2008;

Leyland et al., 2007; Sridharan et al., 2007). While such research often assumes that the relationship between deprivation and mortality is homogeneous and uniform over space, the presence or absence of heterogeneity in the deprivation-mortality relationship can provide important clues to the mechanisms and contexts through which deprivation can impact mortality (Birch et al., 2000; Maurer, 2007), and inform how to respond to deprivation, and how to shape policy aimed at reducing health inequalities. For example, should efforts to address deprivation be focused not only on areas of high deprivation but also on areas that have high levels of deprivation and strong relationships between deprivation and mortality? *Delivering for Health*, a key health policy document in Scotland, promotes health interventions in the poorest areas as one approach to reducing health inequalities: "...NHS Scotland can do more itself to break the link between deprivation and poor health. We need not only a sustained effort to promote good health and good health care, but also to target our resources at areas of greatest need." (Scottish Executive, 2005). While most work on heterogeneity in the relationship between risk factors and health has been at the individual level (Bhopal et al., 1999; Bhopal, 2002; Fletcher, 2007), recent research has considered the relationship of deprivation to health (broadly defined) both spatially and across multiple levels (Morenoff et al., 2001). Understanding variation at the area level requires both a theoretical understanding and methodological approaches that can model and estimate such heterogeneity, but methods commonly used to model the relationship between deprivation and mortality frequently assume that the relationship is uniform across space (Higgs et al., 1998).

Deprivation and Mortality in Scotland

The question addressed in this paper is whether the relationship between deprivation and mortality is the same irrespective of the spatial context? There is a growing body of research exploring the contextual relationship between deprivation and mortality. One of the assumptions that is often made in modeling the relationship between deprivation and mortality is that this relationship will remain the same across space. There is little justification presented in the literature as to why the deprivation-mortality relationship will be homogenous across space. The homogeneity of this relationship over space is an empirical question and most of the published literature does not formally test this relationship. There are some good reasons for the deprivation-mortality relationship to be homogenous over space. Within this viewpoint, the impact of deprivation on mortality is so strong that contextual factors might do little to alter this relationship. There is some evidence on the stability (both temporally and spatially) of the deprivation and mortality relationship. For example, a recent paper finds temporal stability in the relationship between deprivation and mortality over a hundred years: Gregory (2009, b3454) concludes, “There was no evidence of a significant change in the strength of the relation between deprivation and mortality between the start and end of the 20th century. Despite all the medical, public health, social, economic, and political changes over the 20th century, patterns of poverty and mortality and the relations between them remain firmly entrenched.” Dorling et al. reach a similar conclusion (2000, p. 1547): “Contemporary patterns of some diseases have their roots in the past. The fundamental relation between spatial patterns of social deprivation and spatial patterns of mortality is so robust that a century of change in inner London has failed to disrupt it.”

In this paper, the assumption that the relationship between deprivation and all-cause mortality essentially remains constant in the West and the Rest of Scotland represents the null hypothesis (Scenario 1 in Figure 1 describes such a relationship that is not moderated by the underlying context).

Figure 1 here

The rival hypothesis expects this relation to be spatially heterogeneous, i.e. varying between regions (e.g., stronger in the West than the rest of Scotland). This rival hypothesis is motivated by growing evidence of the contextual moderators of the deprivation-mortality relationship. Scenario 2 in Figure 1 describes the important role of context in moderating the relationship between deprivation – in region 1, the relationship between deprivation and mortality is strong, while in region 2, the relationship between deprivation and mortality is weak (the size of the middle box provides a measure of the strength of the relationship). The implication of a finding that is supportive of scenario 2 is that the impact of deprivation will vary depending on the context. This has implication for the mechanisms that connect deprivation to mortality.

Evidence for the possible complexities of mechanisms linking deprivation and mortality can be found in Macintyre et al. (2008). Macintyre et al. (2008, p. 900) conclude: "Thus it appears that in the early 21st century access to resources does not always disadvantage poorer neighourhoods in the UK. We conclude that we need to ensure that theories and policies are based on up-to-date and context-specific empirical evidence on the distribution of neighbourhood resources and to engage in further research on interactions between individual and environmental factors in shaping health and health inequalities." Macintyre (2007) finds that some poorer areas can also have greater environmental resources that can moderate the toxic impacts of deprivation: "Thus there are understandable contextual reasons for a variety of distributional patterns, and it would be sensible not to assume that environmental resources are more likely to be concentrated in better off areas and unavailable to those in poorer areas."

Contextual factors considered in the literature include urban vs. rural location (Levin and Leyland, 2006), ethnic groups (Tobias and Yeh, 2006), and country contexts (van Lenthe et al., 2005). A promising environment for investigating heterogeneity in the deprivation-mortality relationship is provided by the case of Scotland. All-cause mortality is higher in Scotland than in most other Western European countries of comparable wealth (Hanlon et al., 2001). A recent assessment of Scotland's mortality experience concluded that the expectation of life for Scottish men and women in 2006 was, respectively, around one year and two years lower than the European Union average (Registrar General for Scotland, 2007). Within the UK, life expectancy in Scotland over the period 1995-1997 was lower than for the other three countries of Great Britain (i.e. England, Wales and Northern Ireland) (Griffiths and Fitzpatrick, 2001). Standardized mortality ratios (SMRs) for Scotland rose relative to those for England and Wales from the 1980s onwards (Hanlon et al., 2005). Attempts to account for Scotland's poorer mortality experience relative to the rest of the UK have highlighted differences in deprivation as a possible explanatory factor (Carstairs and Morris, 1989). However, an analysis of patterns of deprivation between 1981 and 2001 concluded that from 1991 onwards, measures of deprivation no longer explained most of the excess mortality observed in Scotland (Hanlon et al., 2005).

Appreciable variation is evident in the geographical distribution of mortality within Scotland itself. Four Scottish Council areas (out of a total of 32) recorded SMRs in 2006 which were more than 10 percent higher than the Scottish average (Registrar General for Scotland, 2007). All four of these areas are located in West Central Scotland. The area with the 'worst' mortality experience in 2006 – Glasgow City – recorded an SMR that was 26 percent higher than the Scottish average (itself around 14 percent above the UK average; Registrar General for Scotland, 2007). The persistently poor mortality experience of Glasgow City is illustrated by the fact that, in the period from 1995 to 1997, life expectancy for males in this area was lower than the all-UK figure for 1966 (Griffiths and Fitzpatrick, 2001). Consideration of cause-specific mortality confirms the adverse experience of Council areas in the West of Scotland. In the period 2001 to 2005, male death rates from heart disease were more than 20 percent above the Scottish average in Glasgow City, Inverclyde and West Dunbartonshire. Six areas in the West of Scotland were included in the ten worst authorities in Scotland for male mortality from cerebrovascular disease in the same period. Male mortality from lung cancer in Glasgow City was particularly marked, the death rate rising to 59 per cent above the national average for the period 2001-05 (Registrar General for Scotland, 2007).

Spatial Approaches to Studying Area Level Deprivation and Mortality

One promising approach to elucidating the determinants of the seemingly anomalous mortality profile of the West of Scotland involves the adoption of spatial data analysis (Sridharan et al., 2007; Anselin, 1995; Haining and Wise, 1997). Local small-area variation in mortality lends itself readily to investigation via spatial analysis, the functions of which include detecting spatial patterns in data and formulating hypotheses based on the geography of the data (Haining and Wise, 1997). In the specific context of Scotland, Sridharan et al. (2007) recently identified strong spatial relationships (at the level of the postcode sector) between deprivation and mortality, concluding that area-level mortality is influenced not only by deprivation within a specific area, but also possibly by levels of deprivation in neighbouring areas. These findings justify the continued use of spatial methods to further elucidate the determinants of the heterogeneity of mortality levels observed within Scotland.

The Regions of Scotland

When investigating geographical variations in mortality within Scotland (in particular, the poor mortality experience of the West)[1], regional differences in factors plausibly associated (not necessarily causally) with differential mortality rates must be considered. One such factor is the nature of regional commercial activity, past and present. The city of Glasgow formerly hosted Scotland's greatest concentration of heavy industry, but (in common with the West of the country generally) experienced de-industrialisation on a massive scale in the latter half of the 20th century (Walsh et al., 2008). In contrast, other regions were (and remain) markedly less industrial in character. Apart from its commercial history, a second distinctive feature of the West relates to religion, which in the Scottish context is closely intertwined with a number of potentially important social and cultural constructs. In the West of Scotland, a high proportion of the population is of Catholic faith; data from the 2001 census indicating that 29.2% of residents of the Glasgow City local authority area are Catholic (Pacione, 2005). Similar proportions are found elsewhere in the West of the country, e.g. West Dunbartonshire (33.4%) and Inverclyde (35.8%). The prevalence of Catholicism in these areas is markedly higher than in most other areas of Scotland. This disparity is potentially relevant to regional mortality, because Catholic religion in Scotland mainly indicates Irish ancestry (Abbotts et al., 2001; Paterson and Iannelli, 2006), and Irish background is associated with disadvantage in health (Abbotts et al., 1997) and socio-economic position (Abbotts et al., 1999). Such findings raise the possibility that Scottish inter-regional differences in religious affiliation (especially the 'West versus the rest' contrast) may act as a proxy for variations in other behavioural, cultural or lifestyle factors which potentially relate to observed mortality differentials.

Although not treated in great depth in the present study, one further factor with possible relevance to regional mortality differences is the influence of local meteorological conditions. One theory with plausible relevance to the Scottish mortality experience involves the 'inverse housing law' identified by Blane et al. (Blane et al., 2000; Mitchell et al., 2002). This postulates that areas of the UK that experience harsher local climatic conditions also have poorer housing, and parts of Scotland (including the West) are identified as suffering both poor climate and poor housing (Blane et al., 2000, p. 746, Figure 1). This pattern of association between climate and housing conditions exhibits relationships with both respiratory health (Blane et al, 2000) and hypertension (Mitchell et al., 2002). Such effects as the Inverse Housing Law indicate that future spatially based investigations into regional variations in mortality in Scotland may benefit by including local climate/weather conditions.

Hypothesis

In summary, it may reasonably be asserted that regional differences in Scotland (specifically, a contrast between the West and the remainder of the country) are evident in a number of factors: commercial / industrial, religious / cultural and (possibly) climatic. Consequently, the contexts in which the (unknown) processes shaping any hypothesised relationship between deprivation and mortality operate are not uniform. Given this heterogeneity of regional context, it is reasonable to expect that the nature of the observed association between deprivation and mortality may differ between the West and other regions. The hypothesis examined in this paper is that the relationship between deprivation and mortality differs statistically across the regions of Scotland. Based on the above arguments, we anticipate the

[1] The West region consists of Ayrshire & Arran, Argyll & Clyde, Forth Valley, Glasgow, Lanarkshire.

coefficient linking deprivation to mortality in the regression models to differ statistically between the West and other regions of Scotland. The null hypothesis to be rejected suggests that, on average, the relationship between deprivation and all-cause mortality remains constant across regions, i.e. is not affected by regional context. In this case one would expect to find a similar relationship in the West and the Rest of Scotland despite the differences between the two regions outlined above.

METHODOLOGY

In summary, the methodology applied in this paper is designed to tease out the spatial effects (spatial autocorrelation and spatial heterogeneity) that characterize the relationship between deprivation and all-cause mortality in Scotland. To do so, we start with exploratory spatial data analysis (ESDA) and descriptive statistics to get an initial sense of the spatial distribution of mortality and deprivation, the extent of local and overall clustering of these values, and the bivariate correlation. This exploratory stage is formalized in a diagnostic test of spatial dependence of the Ordinary Least Squares (OLS) residuals to detect potential patterns of spatially correlated values (in either mortality rates or in the error term) and the subsequent specification and estimation of a spatial lag model through spatial two-stage least squares with instrumental variables for the spatial lag term. To test for spatial heterogeneity in the deprivation-mortality relationship, this model is extended to include so-called spatial regimes, the West and the Rest of Scotland.

Exploratory spatial data analysis (ESDA) is a subset of exploratory data analysis (EDA) that focuses on the distinguishing characteristics of spatial data, including spatial heterogeneity and spatial autocorrelation - the phenomenon where locational similarity (observations in spatial proximity) is matched by value similarity (attribute correlation) (Anselin, 1988). The point of departure in ESDA is the same as EDA, namely to use descriptive and graphic statistical tools to discover patterns in data by imposing as little prior structure as possible (Tukey, 1977).

The purpose of this analysis is 1) to better understand in how far the relationship between mortality and deprivation is consistent between the West and other regions of Scotland, 2) to assess the extent of clustering in values between a postcode and its neighbors and to identify where these clusters are located (local and global Moran's I), and 3) to explore linkages between statistical and geographic representations of the data (e.g., between a bivariate scatter plot relating deprivation and mortality and a postcode map depicting the proportion of males).

Global and local Moran's I are used as the statistics to identify the extent of overall clustering and the location of the local clusters (Anselin 1995). [2] While the global Moran's I statistic is a measure of overall clustering of SMRs and deprivation in Scotland based on the measure's value in each postcode and the average of its neighbouring postcodes, it does not indicate the location of clusters. To identify clusters of high and low values of SMRs and deprivation, we apply so-called Local Indicators of Spatial Association (LISA; Anselin, 1995). The local and global Moran's I statistics compare the observed association between a value in a given postcode and its neighbours to those of a spatially random reference distribution. A neighbouring postcode can be defined in various ways through a so-called spatial weights matrix

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[2] The global measure of Moran's I is defined as:

$$I = \sum_i \sum_j w_{ij}.(x_i - \mu).(x_j - \mu) / \sum_i (x_i - \mu)^2$$

where w_{ij} is the row-standardized contiguity matrix, x_i is the risk scale measure at county i, and x_j is the risk scale measure at county j, and □ is the average level of risk.

The local measure of Moran's I is defined as:

$$I = \frac{(x_i - \mu)}{\sum (x_i - \mu)^2} \sum_j w_{ij}.(x_j - \mu)$$

W. In this paper, we define a postcode's neighbour in terms of a shared corner or border (queen contiguity matrix) – i.e. if a postcode shares any segment of its border with another postcode, the two are considered neighbours. Identifying statistically significant clusters avoids the problem of over-identifying patterns that is associated with merely eyeballing spatial concentrations on a map. These ESDA methods are implemented through GeoDa (Anselin et al., 2006), a free program that provides a user-friendly environment for ESDA and spatial regression methods.

To test for spatial dependence in a multivariate regression context, diagnostic tests are used to determine whether spatial autocorrelation is present in the OLS residuals. The null hypothesis here is that of spatial randomness, in other words, that SMR values in a given postcode are not related to those in neighbouring postcodes. This paper utilizes Lagrange Multiplier (LM) tests that point to either a lag or error model alternative as a better fit for the data if the OLS residuals are found to be spatially autocorrelated. Two classic specifications to model spatial autocorrelation in this context include a spatial lag model and a spatial error model (Anselin 1988). As discussed in the results section, the LM Lag test was significant for the data used in this paper, pointing to a spatial lag model as the best fit for the data.

The spatial lag model specification adds the average of neighboring values of the dependent variable as a predictor to the model, as shown in the following mixed regressive spatial autoregressive model specification:

$$y = \rho W y + X\beta + \varepsilon \qquad (1)$$

where y is the vector of observations on the dependent variable, Wy is the spatial autoregressive and X the regressive component of the model (hence the name), ρ is the spatial autoregressive parameter and ε is the vector of regression disturbances (i.i.d). W is an N x N matrix (by convention, W is row-standardized and does not define an observation as its own neighbour). Wy is typically referred to as the spatial lag of y. If the spatial lag of W (i.e. the average neighbors of y) is significant, this can have different reasons. It can point to a process of contagion where neighbors influence the center and vice versa or can be due to spatial measurement error where, e.g., the spatial extent of a postcode, which represents an administrative unit for mail delivery purposes, does not correspond well to the spatial extent of the processes that are related to mortality rates. In the first case, values for neighbouring postcode sectors can be related because they influence each other. In the latter case, they are correlated because of a mismatch in scale.

Because the spatial lag term is correlated with the error term the spatial lag model needs to be estimated through specialized spatial methods (the use of OLS to estimate this model would generate biased and inefficient coefficients). In this paper, we estimate this model through spatial two-stage least squares, which uses the first order of the spatially lagged independent variables (WX) as instruments to estimate the coefficient for the spatially lagged dependent variable Wy (for details, see Kelejian and Prucha 1998 and Anselin 1988). One of the other estimation problems that needs to be addressed is related to the variation in population size between postcode sectors: Population sizes range from 1,000 to 20,512 with a mean size of 5,949 persons per postcode sector (and a standard deviation of 2,994 persons; postcode sectors with populations smaller than 1,000 were excluded from the analysis). This variation is problematic because it is related to variance instability in mortality rates across postcodes, i.e it means that the mortality rates are associated with varying degrees of precision. There are different approaches to addressing this variance instability problem in the literature. Since in this context, the problem is essentially one of variation in the precision of the estimate, we estimate all models with standard errors that are robust to heteroskedasticity (White-adjusted).

The spatial lag model specification is based on a single set of coefficients for all of Scotland, i.e. it is a model with beta values that are assumed to be constant across regions. To incorporate a test of spatial heterogeneity in the association between deprivation and mortality, the spatial lag model specification is extended to include so-called spatial regimes (Anselin 1990). The spatial regimes model allows the covariates and the residual covariance to vary across regions (West vs. Rest of Scotland). In essence, separate coefficients are estimated for the two regimes: West Scotland and the rest of Scotland (SE-North Scotland). This is similar to estimating a separate model for each region with two important differences: 1) the spatial regime approach estimates the standard errors within each regime based on the whole dataset, which results in more precise standard error estimates, and 2) a spatial chow test evaluates whether there is a statistical difference between the coefficients in each regime.

A framework of spatial regimes has been applied to a number of problems: regional differences in the effects of structural covariates on homicide rates (Baller et al., 2001), spillover of academic knowledge (Anselin et al., 2000), regional convergence processes (Ertur et al., 2006), and dynamics of urban violence (Morenoff et al., 2001). The spatial regimes model provides important clues to the (unobserved) mechanisms by which deprivation is connected to mortality. Note that the absence of heterogeneity is in itself indicative of the mechanism that connects deprivation to mortality.

The following notation is used for a linear spatial lag model with spatial regimes (Anselin 1988):

$$y^* = \rho Wy + X^* \beta^* + \varepsilon^* \qquad (2)$$

where y is the vector of observations on the dependent variable, Wy the spatial lag term, X is the matrix of exogenous variables, β is the vector of regression parameters (ρ is the spatial parameter of Wy, which is estimated for the model as a whole), and ε is the vector of regression disturbances (i.i.d). The asterisk indicates that each parameter contains subgroups of observations associated with the two regimes. To illustrate, Model 3 in Table 2 contains SMRs for 840 postcodes, 13 regressors, and two regimes (West and Rest). In the West Scotland regime, the regressors will have nonzero values for this regime and zero values for the Rest regime. Conversely, the regressors for the Rest regime contain non-zero values for the Rest regime and zero values for the West regime.

A spatial variant of the Chow test (Anselin 1990) assesses if the null hypothesis of spatial stationarity holds against the alternative of spatial heterogeneity. Specifically, it tests if the coefficients for the same variable remain constant across regions or not and if there is a statistical difference between regions for the model overall. Table 2 reports the Spatial Chow value and significance level for the model overall at the bottom of each model. The values and significance levels associated with the Spatial Chow test for the stability of individual coefficients across regions is reported as a separate column for each model in this table.

Data and Models

The data for this study were obtained from ISD Scotland. Data on all-cause mortality originate from the Office for National Statistics and General Register Office for Scotland while the other measures in the study are from the 2001 census (Registrar General for Scotland, 2007). In this study we focus on the spatial arrangement of communities at the finest geographical scale possible in order to avoid some of the 'smoothing' of population characteristics which may occur when using physically large areal units. However, physically small areal units often contain small residential populations, few deaths and correspondingly unstable mortality rates. Scotland's fragmented landscape also presents challenges for analyses focused on the spatial arrangement of population characteristics; administrative units are often physically split (across islands for example). For this exploratory study we therefore restricted the statistical analyses to postcode sectors with a population of 1,000 or more and to a single physical segment for each sector. This results in a total of 840 postcode sectors (379 in the West and 461 in the rest of Scotland) to include in the analysis.

Since the question of interest is whether the relationship between deprivation and mortality varies between West Scotland and the other Scottish regions, the two key measures in the paper include the 2001 Carstairs score (a measure of deprivation) and standardized mortality ratios. These measures are aggregated at the postcode level. The Carstairs score consists of four standardized census variables: adult male unemployment, lack of car ownership, low social class and overcrowding (McLoone, 2004; Morgan and Baker, 2006). The standardized score for each of the variables is first calculated and then the Carstairs score is computed by summing each of the individual standardized scores. Note that under this method of calculation, both negative and positive values of Carstairs are obtained.

All-cause mortality by age group and sex is computed as the annual number of deaths within an age group per the population in that group. Mortality ratios for deaths at ages under 75 years are standardized using age and sex specific death rates for Scotland for age groups 0 to 4, 5 to 14, 15 to 24, 25 to 34, 35 to 44, 45 to 54, 55 to 64, 65 to 74 years. SMRs were based upon deaths registered during a three-year period around the 2001 census and population denominators from the 2001 census. The exclusion of deaths at ages 75 years and over focuses the analysis on premature mortality. Several studies have found premature mortality to be more closely associated with area deprivation than deaths at older ages (Cartairs and Morris, 1989) although this finding is disputed (O'Reilly, 2002). Hanlon et al's (2005) analysis also suggests that the proportion of excess deaths in Scotland in comparison to England and Wales are relatively lower at age 75 years and over than at younger ages. The exclusion of deaths at ages 75 years and over will also reduce the influence that the presence of nursing homes may have on the death counts within small areas (Williams et al., 2004). Data on the rainfall and temperature were at the postcode sector level (New et al, 2000).

The model of the deprivation-mortality relationship in the two Scottish regions includes a series of control variables that are expected to affect mortality rates. The base spatial regime model specification used in this paper is shown in equation 3:

$$SMR^* = \alpha^* + \rho Wy + \beta_1^* CAR^* + \beta_2^* AGE^* + \beta_3^* MALE^* + \beta_4^* URBAN^* + \beta_5^* TEMP^* + \beta_6^* RAIN^* + \varepsilon^* \tag{3}$$

where the dependent variable, SMR, is modelled as a linear function of an intercept, deprivation (CAR), a spatial lag term Wy, a matrix of AGE variables (percentage of population in age groups 0-4, 5-14, 15-24, 25-34, 35-54, 55-64, 65-74), the percentage of males in the population (MALE), an indicator for the Glasgow, Edinburgh, Aberdeen and Dundee urban areas (URBAN), mean temperature (TEMP), and annual rainfall (RAIN). Each variable is associated with a beta coefficient (in the case of Wy, ρ is used) whereas alpha represents the coefficient of the constant and ε is the error term.

The asterisk indicates that the model is estimated for two regimes: West and Rest

(Southeast-North).[3] These regimes are based on the classification of the three Health Boards (West, Southeast, and North) used by the Cancer Team of Information Services Division (ISD) Scotland.[4] The West region consists of Ayrshire & Arran, Argyll & Clyde, Forth Valley, Glasgow, Lanarkshire. The North region includes Grampian, Highland, Orkney, Shetland, Tayside, Western Isles; and the Southeast region contains Borders, Fife, Lothian, Dumfries & Galloway. The North and the Southeast region were consolidated to create the "SE-North Scotland category" (also abbreviated as "Rest" in comparison to "West"). Note that the coefficient for the spatial lag term is estimated for the model as a whole (as opposed to each region) in the regimes specification.

To present separate results for the models discussed in the methodology section and generate results for different dimensions of the research question (Table 2), we estimate seven versions of the model presented in equation 3 (plus a base OLS model to obtain the LM test results):

Two base models for the entire Scotland study area:

1. Model 1: OLS with robust (White-adjusted) standard errors, no spatial lag term
2. Model 2: Spatial lag model: Spatial 2SLS with instruments and robust standard errors

Five versions of the spatial lag model (Model 2):

3. Model 3: Spatial Regimes: West vs. Rest, one deprivation variable (assuming a linear relationship between deprivation and mortality)
4. Model 4: Model 3 but with low and high deprivation (medium excluded base), allowing for a non-linear relationship between deprivation and mortality
5. Model 5: Model 4 with male SMRs as the dependent variable

[3] For comparison purposes, Model 7 separates the Rest region into North and Southeast regions.
[4] For more information, see http://www.isdscotland.org.

6. Model 6: Model 4 with female SMRs as the dependent variable
7. Model 7: Model 4 with 3 regimes: West, Southeast and North

Table 2 presents the Spatial Chow test values and significance levels for all spatial regime models in two versions: As a test of the differences between regimes for the overall model (bottom of Table 2) and as a test for the stability of individual coefficients across regimes (last column for each model). For Model 1 (OLS), the R^2 is reported. For the other spatial lag models, a pseudo R^2 value is used (the ratio of the variance of the predicted values/ variance of the observed values for Y).

RESULTS

Exploratory Spatial Data Analysis

To summarize the results upfront, the initial exploratory spatial data analysis reveals concentrations of high SMR and deprivation values (hotspots) in the West of Scotland and concentrations of low values (coldspots) for both variables in the Rest of the country. The question is whether this spatial heterogeneity in the distribution of SMR and deprivation values in the two regions is associated with a different relationship between mortality and deprivation (in terms of the intercept or slope of their respective coefficients). It turns out the answer is no – we cannot reject the null hypothesis of spatial homogeneity in the deprivation-mortality relation in Scotland for the data analysed in this paper. As the subsequent spatial modeling results will demonstrate, the relationship between deprivation and mortality remains essentially constant in the West versus the Rest of Scotland, despite the contextual differences that characterize the two regions. This result also holds when the regions are broken into West, Southeast and North, and for male and female SMRs as the dependent variables.

As described in Table 1, the SMR for the overall population, as well as the SMRs for males and females, are considerably higher in the West as compared to the Rest of Scotland. Similarly, the levels of deprivation are also considerably higher in the West as compared to the rest of Scotland. Note that the pattern of results in Table 1 provides little clues regarding heterogeneity in the relationship between deprivation and mortality.

To get a better initial sense of the spatial distribution of SMR and deprivation, Figures 2 and 3 provide maps of these measures by postcode (West Scotland is shown in the inset).

(insert Figure 2 and 3 here)

The insets for West Scotland appear to contain especially high SMRs and high levels of deprivation (postcode sectors with populations less than 1,000 are marked as "postcodes with insufficient data"). However, a visual inspection of these maps cannot address the question of whether these apparent concentrations represent statistically significant local clusters. This question is explored in Figures 4 and 5, which present maps of local indicators of spatial association (as discussed above) for SMR and deprivation in West Scotland and the remaining regions. Two types of spatial association are highlighted: Clusters of high values (hotspots) and clusters of low values (coldspots).[5]

(insert Figures 4 and 5 here)

What this analysis demonstrates is that hotspots of both all-cause mortality and deprivation are concentrated in West Scotland while coldspots of both are primarily found in the

[5] Note that the clusters in Figure 3 and 4 include the cluster core and neighbouring postcodes. A queen contiguity criterion is used to define neighbours, i.e. postcodes with shared borders or corners. Because postcode sectors with population sizes below 1,000 were excluded from the sample, a lot of sectors no longer shared borders with nearby

remaining regions. This finding is quantified in Figures 6-8, which —for the West vs. the Rest of Scotland— compare the proportion of LISA cluster cores for SMR clusters (Figure 6), deprivation clusters (Figure 7) and clusters of two separate variables: SMRs in a given postcode with the average deprivation index of its neighbours (Figure 8). The latter examines the bivariate spatial relationship between deprivation and the neighboring values of mortality for both Western and other regions.

(insert Figures 6-8 here)

While the proportion of insignificant, i.e. non-clustered, postcodes is comparable between the West and Rest of Scotland in all three cluster cases, the proportion of hotspots and coldspots reverses in all three cases. Clusters of high SMRs and deprivation are concentrated in West Scotland: About a quarter of all postcodes in this area constitute the core of a hotspot. In contrast, this is only true for 2-3 percent of postcodes in the Rest of Scotland. The pattern of coldspots mirrors this finding: Low values of SMRs and deprivation are clustered in the Rest of Scotland at 18-21%, while such coldspots are only found in 2% of the cases in West Scotland. The same pattern is true for clusters of SMRs and neighbouring deprivation.[6]

In anticipation of the next modelling stage, two additional descriptive statistics are added: Results from the global Moran's I test and those from the bivariate correlation between deprivation and all-cause mortality. The global Moran's I test indicates strong clustering of both the standardized mortality ratios as well as the deprivation measure (Carstairs index) in Scotland overall. Figure 9 compares two so-called Moran scatterplots where the Moran's I statistic is visualized as the regression slope of a spatially lagged variable (W_smrtfin and W_Carstairs on

postcodes (in addition to real islands). To avoid disconnected postcodes, we converted the postcode geographic file to Thiessen polygons. This queen contiguity weights matrix is used for the spatial lag analysis throughout the paper.

[6] Note that the percentages do not add up to 100% since spatial outliers, i.e. postcodes with high values surrounded by low values, and vice versa, are not included in the table.

the y-axis) and the original variable.

(insert Figure 9 here)

Within each scatter plot, the global Moran's I statistic for SMRs and the Carstairs index for Scotland overall (top left value in scatter plot) is compared to those where West Scotland is excluded (top right in scatter plot). This allows for a comparison of slopes between the two regions. The variables are SMR (left) and deprivation (right). The spatial lag of these variables is, respectively, the average standardized mortality ratio and the deprivation index of each postcode's neighbouring postcodes.[7]

In Scotland, all-cause mortality and deprivation measures in a given postcode are significantly clustered with those in neighbouring postcodes (Moran's I = 0.46, which is highly significant). This can include clustering of low and/or high values. When West Scotland is excluded, Moran's I is 0.29 for SMRs and 0.32 for Carstairs (both still highly significant). However, what this suggests is that both variables are more strongly spatially clustered throughout West Scotland compared to the rest of Scotland. A diagnostic test of spatial dependence will later be applied to test if spatial autocorrelation is present in the OLS residuals.

Moving beyond a univariate analysis to bivariate relationships, the Pearson correlation for SMR and Carstairs is examined. It turns out to be very similar for the West and Rest regions. Strong associations are observed for both the regions with close to 65% of the variance in SMR explained by Carstairs: For the Western region the correlation coefficient between SMR and Carstairs is 0.83 ($p < 0.01$); in the remaining region the correlation coefficient is 0.81 ($p < 0.01$).

Spatial Modeling

[7] The results are robust to alternative neighbour definitions such as six nearest neighbours based on postcode centroids.

To formalize these exploratory results through multivariate spatial regression modeling, the next step is to estimate the model in equation 3 with OLS (without the spatial lag term and the regimes) to obtain the LM test results for spatial dependence in the OLS residuals. The LM-Lag test result (19.09) turned out to be more statistically significant (p-value: 0.000012) than the LM-Error test result (12.84 with p-value of 0.00034). This result indicates that the OLS residuals are spatially autocorrelated in this model and thus motivates the estimation of the spatial lag specification in Models 2 to 7. Table 2 summarizes all model results. The spatial lag model for all of Scotland (Model 2) and that for the West vs. the Rest with one deprivation variable (Model 3) have the highest pseudo-R^2 values, 74% and 76%, respectively. This explained variation drops to 60-64% for Models 4, 5, and 7 where deprivation is measured in low and high categories. The model has a better fit for male than female SMRs: In the case of female SMRs, the explained variation in SMRs is lowest (Model 6: R^2 = 50%).

(insert Table 2 here)

The main result is that deprivation is the only variable that is significant at the 0.001 level in all models – however, in contrast to the expected spatial heterogeneity in the deprivation-mortality relationship, this relation does not vary between regions in any of the models (none of the values of the Spatial Chow test for differences in the deprivation coefficients across regions is significant). In other words, the null hypothesis that, *ceteris paribus*, on average the same relationship between deprivation and mortality holds across regions cannot be rejected. This is surprising from a perspective that expected the different contexts of the West and the Rest of Scotland to be related to differences in the correlations between deprivation and mortality. It supports research such as Gregory (2009) and Dorling et al. (2000), which found a rather constant relationship between mortality and deprivation across time.

If deprivation (Carstairs) is included as a single variable, assuming a linear relationship with SMRs, the relation is characterized by a coefficient of 8.33 for all of Scotland (Model 2) compared to 8.86 for the West and 8.13 for the Rest of Scotland (Model 3; all significant at the 0.001 level).[8] Since there is no reason to assume linearity in the deprivation-mortality relationship, Model 4 includes separate indicators for whether a postcode is in the bottom or top third of deprivation values.[9] The results indicate that low deprivation is negatively or not related to mortality while high deprivation is positively related to mortality rates in all models at the 0.001 significance level. In other words, there is an inverse relationship between deprivation and mortality depending on whether a postcode falls in the low or high deprivation category. The difference in coefficient values is largest for male SMRs in the West of Scotland (-7.10 for low compared to 31.00 for high deprivation, at a p-value of 0.05; Model 5). This large coefficient gap between low and high deprivation is a result that holds for pooled SMRs when the Rest is separated into the Southeast and North (-5.73 for low vs. 27.22 for high deprivation in the West; Model 7). However, as the Spatial Chow test indicates there are no statistically significant differences in the deprivation parameter estimates between regions in any of the models. The only variables that do differ significantly between regions are some of the age variables: All ages except for the youngest and/or oldest age categories not only are significantly related to mortality but also differ in their relationship with mortality between regions in Models 3, 4, and 6. The gender breakdown by SMR in Models 5 and 6 suggests that these differences in age categories between regions are only significant in the case of female SMRs, not male SMRs.

Essentially, whether or not a postcode falls into one of the four urban areas and climate

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[8] This compares to a coefficient of 9.27 in a misspecified OLS model without the spatial lag term (Model 1).
[9] To create the indicator variables, the deprivation values were sorted in ascending order and grouped into three equal intervals of 280 postcodes. The group with the lowest values represents the low deprivation indicator, the

conditions such as annual rainfall and mean temperature, is, if at all, only significant at the 0.05 level and only for some models. For instance, the urban indicator is only significant for the West if deprivation is measured with the low and high deprivation indicators (Models 4 and 7). Annual rainfall is only significant once (beta = 0.09), in the case of the male SMR model (Model 5). Mean temperature is also significant in this model (beta = 5.51) and in only one other model, the global spatial lag one (beta = 2.79; Model 2). Both of these variables are only significant at the 0.05 level in all cases. The percentage of males in a postcode is not related to mortality in any model except negatively (-2.79 at a p-value of 0.001) in the Southeast of Scotland (Model 7).

Neighbouring SMRs are a highly significant predictor of SMRs in all of the models (at the 0.001 level) where deprivation is broken into low and high categories (coefficients range between 0.38 and 0.43). They have smaller values in Models 2 and 3 (0.11 with p-value 0.01 and a non-significant 0.07) where deprivation is included as a single variable. This suggests that neighbouring SMRs primarily play a role in models where high deprivation is also strongly related with high mortality rates.

DISCUSSION

Many policy and programmatic interventions are planned with an "overall global" understanding of the relationship between deprivation and mortality. This paper argues for a more nuanced understanding of the relationship between deprivation and mortality. Given the contextualized nature of health outcomes, there might be little reason to a priori expect the relationship between deprivation and mortality to be homogenous across space and time.

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group with the highest values the high deprivation indicator and the group with the middle values is excluded as the base.

We had anticipated finding a heterogeneous relationship between deprivation and mortality across the regions of Scotland. To our surprise, the relationship between deprivation and mortality did not differ between the West and the rest of Scotland. This result was consistent with the remarkable temporal stability found in Dorling et al. (2000) and Gregory (2009, b3454): "Even when the effects of modern deprivation are taken into account, mortality patterns from the 1900s still have a significant relation with mortality today and this affects most major modern causes of death."

The practical and troubling questions that the stability in the relationship between deprivation and mortality raises are: What can governments do to interrupt this stable relationship between deprivation and mortality? More broadly, what does this mean for solutions to address problems of deprivation and mortality? Gregory (2009, b3454) describes the implications these results have for addressing health inequities:

> The 20th century has seen widescale reforms aimed at improving living conditions for society in general and the poor in particular. These include the formation of the National Health Service (NHS), the welfare state, regional policy, and many other initiatives. Beyond this there have been large rises in standards of living and huge advances in medicine and our understanding of health more generally. These have undoubtedly led to large increases in life expectancy but seem to have failed to reduce the impact that poverty has on mortality. This is not to say that these policies have been a failure as it is entirely possible that without them health inequalities might have become far worse over time. One thing that is clear is that the difficulties in reducing health inequalities should not be underestimated as these are deep rooted, long term problems."

While we join Gregory in not underestimating the difficulties in the relationship between deprivation and mortality, it still leaves the troubling question: what can one do to change such stable relationships? The inverse care law describes that the availability of health care services are inversely related to individual needs (Hart 1978, Watt 2006). Based on the inverse care law, some individuals/areas with the greatest needs will have very limited access to good health care.

In its coordinating role, governments can attempt to address this by ensuring that the overall health system (or other sectors) reaches individuals who have unmet needs and that there are no systematic differences in unmet need by key socio-demographic groups, etc. However, this is easier said than done. Paying attention to the spatial distributions of interventions is important.

While the problems of the underlying social determinants of inequalities are reasonably well recognized, how to close the inequalities gap is less well understood. Much of the questions we raise above will have implications for how interventions are planned and implemented to address health inequities. Interventions need to be planned with clarity based on a clear framework of responding to health inequalities. Such a framework needs to address the following key issues: Why will this intervention make a difference in health inequalities? Which populations need to be targeted for the intervention? Further, it is somewhat unclear how a single intervention can address both the inverse care law and also the remarkable spatial and temporal homogeneities in the relationship between deprivation and mortality. Perhaps part of the solution will be to explore an inter-sectoral approach to health inequities, which seeks alignment and synergy across multiple downstream and upstream interventions.

While we found a homogenous relationship between deprivation and mortality across regions in Scotland, one of the interesting implications of the methodological approach implemented in this paper has been to start with an expectation of heterogeneity, rather than *a priori* assume a homogenous relationship between deprivation and mortality. Despite the lack of a heterogeneous result, we think an understanding of health and place will require a stronger substantive and methodological focus on heterogeneity. This paper has only examined two regions of Scotland: future research needs to explore, under what community (and policy and programmatic) contexts can we expect a heterogeneous relationship between deprivation and mortality? In much health research, heterogeneity in the linkages between deprivation and health has either been ignored or treated as a nuisance that needs to be controlled for.

Heterogeneity is increasing as an important substantive concern in other fields--for example, Pickett and Cadenasso (1995 p. 331) in an article in *Science* describe the growing relevance of heterogeneity in landscape ecology: "Throughout much of its history, ecology sought or assumed spatial homogeneity for convenience or simplicity; scales that lent an apparent uniformity to the processes under study were emphasized, and heterogeneity was taken as a necessary evil or an unwelcome complication. In contrast, landscape ecology regards spatial heterogeneity as a central causal factor in ecological systems, and it considers spatial dynamics and ecology's founding concern with the temporal dynamics of systems to be of equal importance."

In a similar way, we believe that heterogeneity in linkages between risk factors and health outcomes can help build a better understanding of the "problem space" around health inequalities. Examining the homogeneity or heterogeneity in deprivation-mortality relationships might only be the first step of understanding the pathways by which deprivation influences mortality --the deeper question is why do relationships vary (or not vary) over space? This would require implementing a detailed mixed-methods study to explore the contextual differences in places.

Second, a focus on heterogeneity (or homogeneity) of linkages might also have practical consequences. Exploring the presence of heterogeneity in linkages between deprivation and mortality can help inform the location of interventions. For example, an important research question is: Should interventions be located in places where the relationship between deprivation and mortality are the strongest? Addressing these questions can help plan more spatially targeted interventions. More generally, there has been a more limited focus on what such heterogeneity means for planning interventions. As noted earlier, much of the research assumes homogeneity in the deprivation-health relationships, rather than establish it empirically. An important future research area is how understanding of the presence or absence of heterogeneities in deprivation-health can help respond to health inequalities.

This paper is limited in several ways: We have focused on heterogeneity between spatial units. There is also a need to pay attention to heterogeneity within places, e.g. as argued by Haynes and Gale (2000):

> "Apparent differences between rural and urban associations are therefore not due to the choice of deprivation indices or census areas but are artifacts of the greater internal variability, smaller average deprivation range and smaller population size of rural small areas. Deprived people with poor health in rural areas are hidden by favourable averages of health and deprivation measures and do not benefit from resource allocations based on area values."

In addition, we have used a conceptualization of regime (West and Rest of Scotland) that is both substantively driven and also driven by convenience. Other theoretically informed approaches might also be possible—for example, it might be useful to compare the heterogeneity in the linkages between deprivation and mortality in urban areas with rural areas, or Glasgow with other cities in Scotland. We have implemented a spatial regimes model to study heterogeneity in linkages. Examples of other methodological approaches include the use of Geographically Weighted Regression to study the spatial variation of coefficients across space (Fotheringham et al., 2002; McMillen, 1996) or the application of spatial expansion methods.

In summary, this study demonstrated a role for spatial analysis methods in illuminating one of the central questions of health inequalities research: the relationship between deprivation and mortality. Although the substantive findings are restricted to Scotland, the study was conceived partly as a methodological illustration of the utility of testing spatial approaches.

Such approaches have widespread potential, not only to further elucidate the determinants of mortality (and morbidity) in Scotland, but to investigate a wide range of risk / health associations in many other intra- and international contexts.

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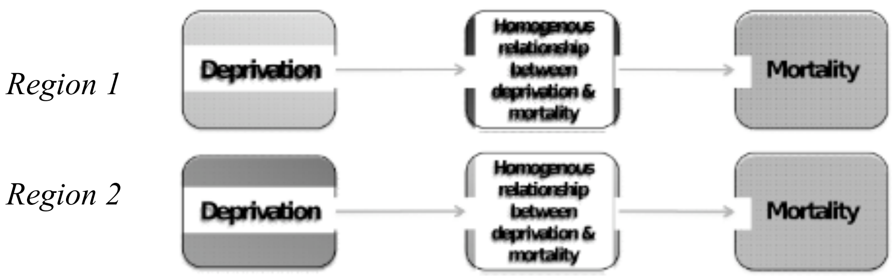
Table 1. Distribution of Variables

	Scotland N = 840		Rest N = 461		West N = 379	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
SMR	99.46	35.96	87.54	27.68	113.96	39.42
SMR Males	100.02	40.25	87.36	30.50	115.42	45.07
SMR Females	98.66	35.58	87.75	29.84	111.93	37.47
Deprivation (Carstairs)	0.99	3.49	-0.05	2.60	2.26	3.99
% Male	48.25	1.69	48.67	1.67	47.75	1.57
% Female	51.75	1.69	51.33	1.67	52.25	1.57
% Age 0-4	5.35	1.09	5.29	1.10	5.43	1.08
% Age 5-14	12.32	2.64	12.21	2.73	12.46	2.51
% Age 15-24	12.28	5.56	12.04	6.62	12.57	3.90
% Age 25-34	13.54	4.30	13.35	4.58	13.77	3.94
% Age 35-54	29.11	3.41	29.36	3.75	28.82	2.92
% Age 55-64	11.15	2.20	11.26	2.36	11.00	1.98
% Age 65-74	8.97	2.31	9.00	2.30	8.93	2.31
% Age 75+	7.28	2.56	7.50	2.52	7.01	2.59
Urban Indicator	0.30	0.46	0.25	0.44	0.35	0.48
Annual Rainfall	91.96	31.61	77.42	28.44	109.66	25.71
Mean Temperature	7.94	0.60	7.76	0.66	8.15	0.42

Figure 1

Scenario 1: Homogeneity in Relationship between Deprivation and Mortality (H_0)



Scenario 2: Heterogeneity in Relationship between Deprivation and Mortality (H_1)

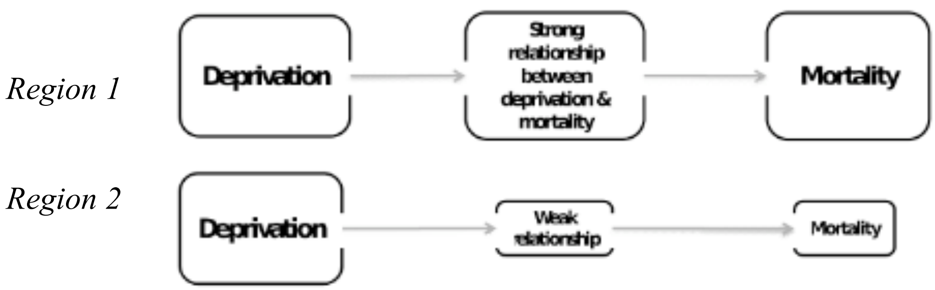


Figure 2. Spatial Distribution of SMRs

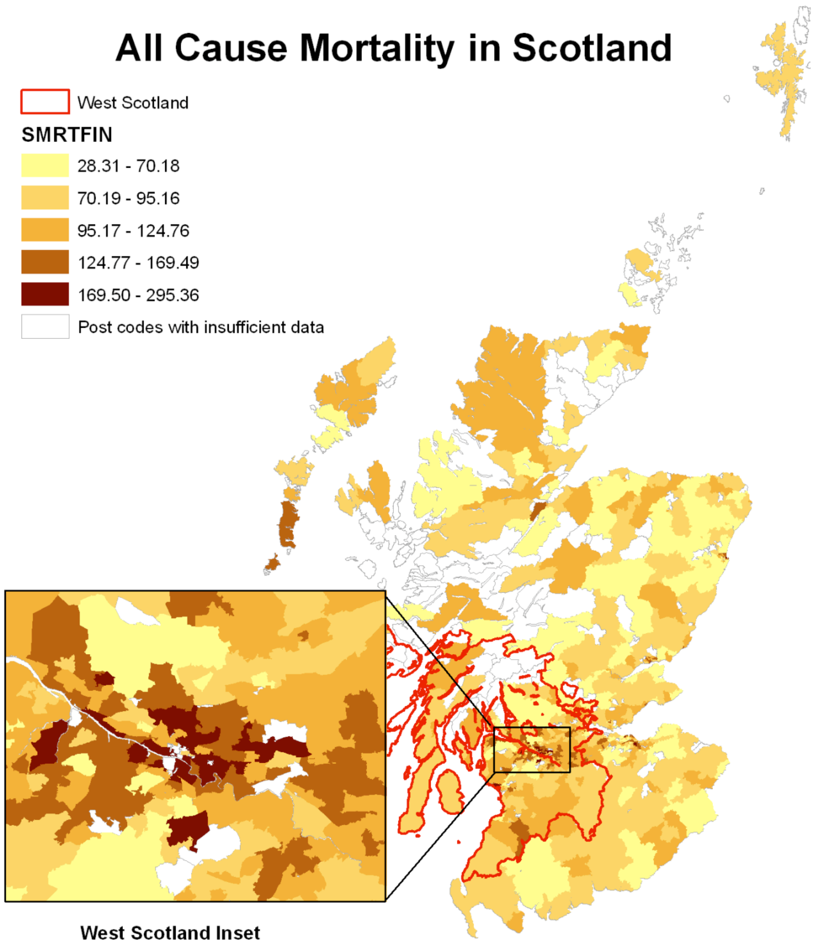


Figure 3. Spatial Distribution of Deprivation

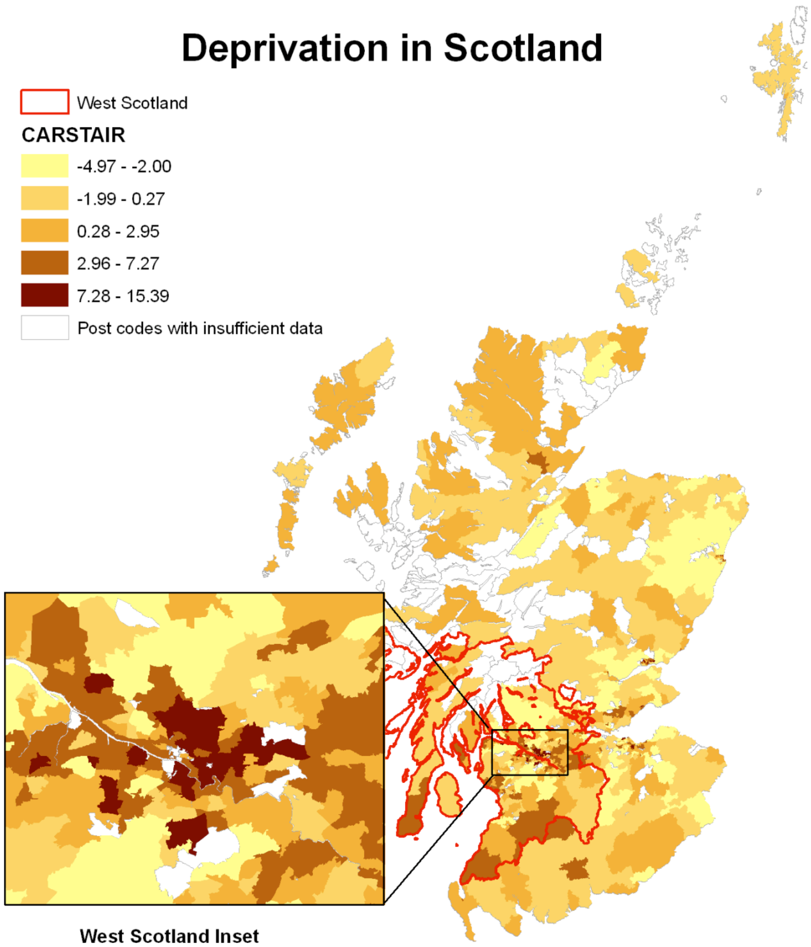


Figure 4. LISA Map of SMRs

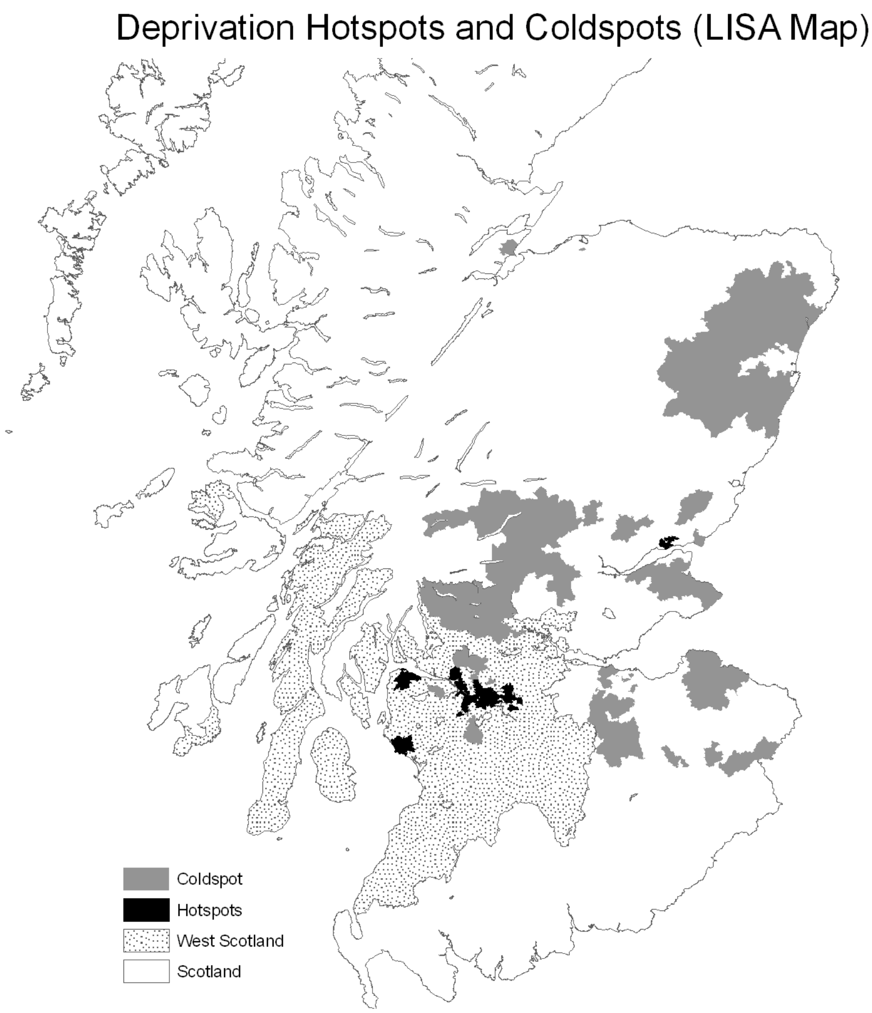


Figure 5. LISA Map of Carstairs

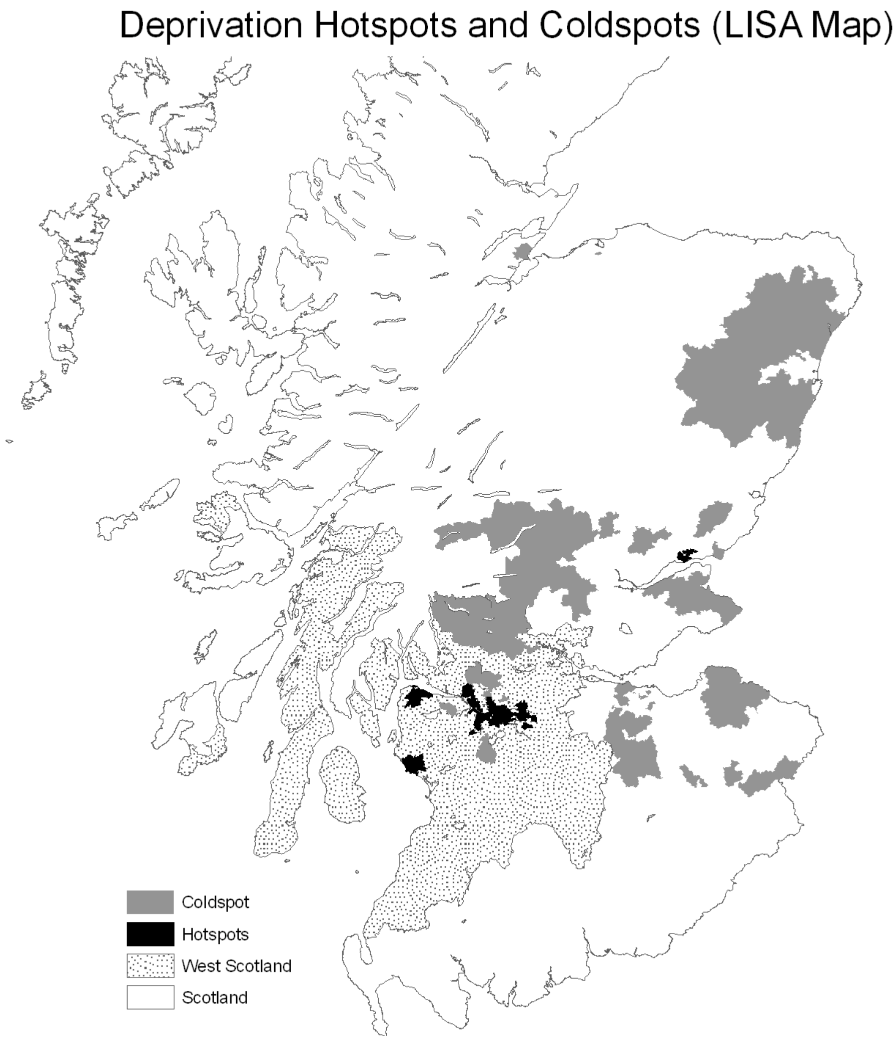


Figure 6. SMR Clusters by Type of Association

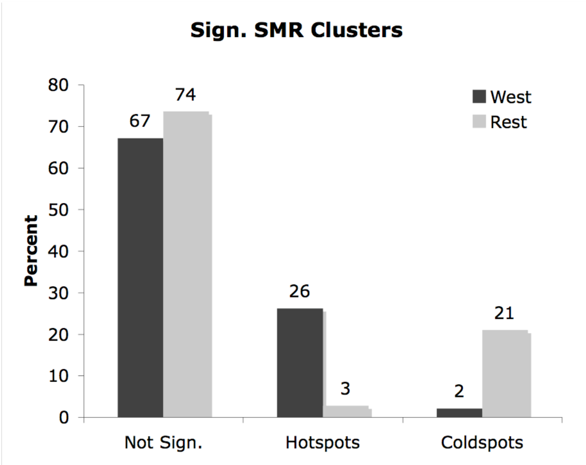


Figure 7. Deprivation Clusters by Type of Association

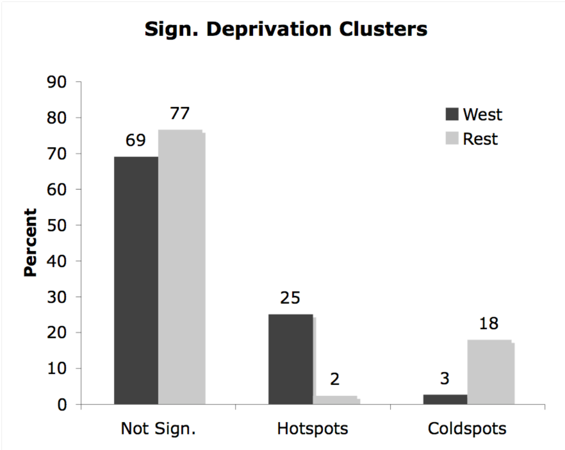


Figure 8. SMR-Deprivation Clusters by Type of Association

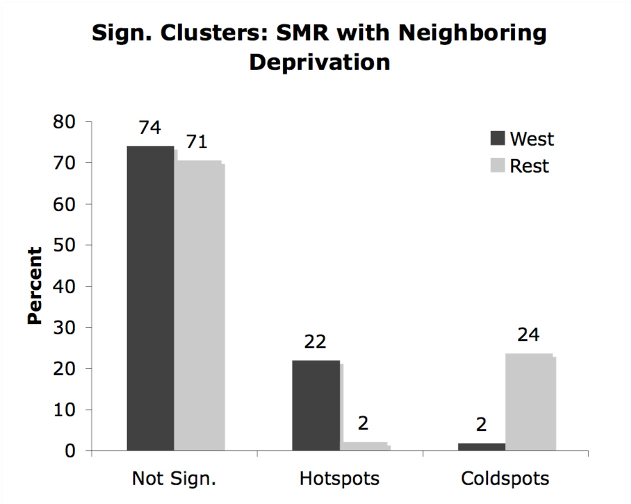


Figure 9. Global Moran Scatter Plots: SMR and Carstairs

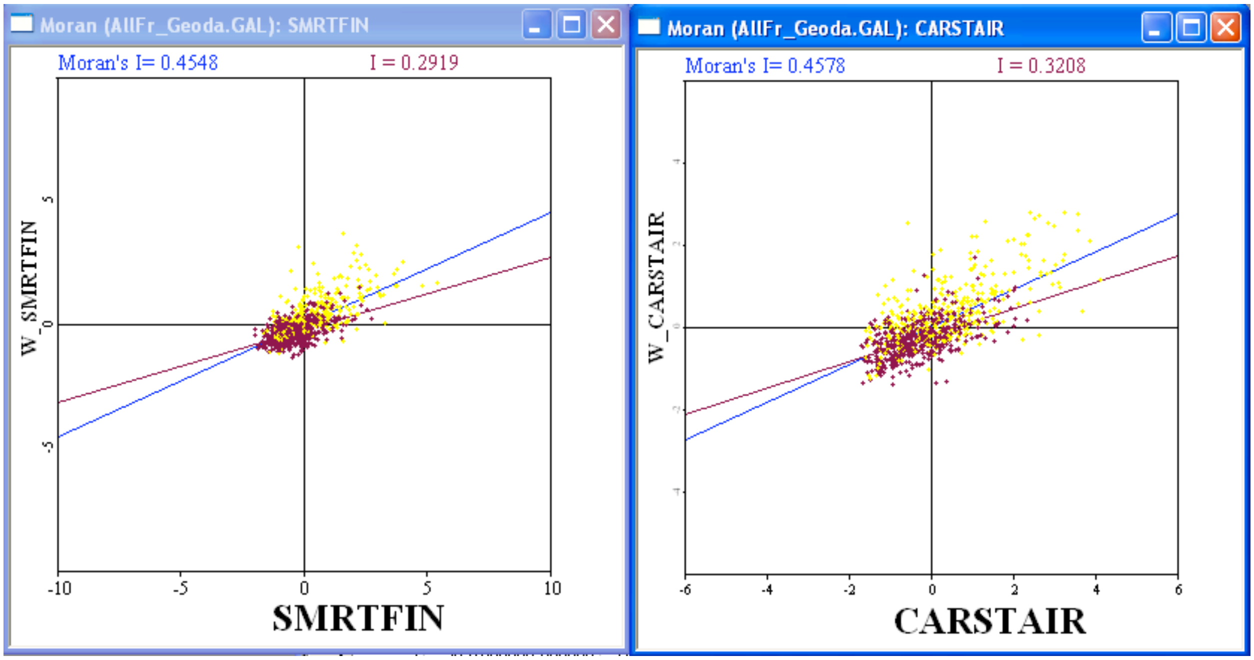


Table 2. Spatial Model Results

	Scotland		West-Rest					
	Robust OLS	Robust Spatial Lag (2SLS/IV)						
	DV: SMRs Total		DV: SMRs Total					
	Model 1	Model 2	Model 3			Model 4		
			West	Rest	Spatial Chow	West	Rest	Spatial Cho
Intercept (1)	119.50 *	129.47 **	232.43 **	95.21	1.99	245.80 *	12.39	3.56
(2)	2.12	2.55	3.06	1.57		2.38	0.18	
Deprivation	9.27 ***	8.33 ***	8.86 ***	8.13 ***	1.37			
	22.97	23.21	19.61	17.39				
Low						-5.86 *	-5.16 **	0.04
						-2.07	-2.67	
High						26.77 ***	21.50 ***	1.49
						8.15	7.47	
% Male	0.83	0.38	1.83	0.22	1.35	0.56	-0.85	0.64
	1.02	0.54	1.67	0.25		0.40	-0.79	
% Age 0-4	-0.67	-0.57	0.27	-1.37	0.58	0.42	0.40	0.00
	-0.57	-0.51	0.16	-1.03		0.18	0.26	
% Age 5-14	-3.05 ***	-2.12 **	-4.78 ***	-0.47	12.28 ***	0.56	3.74 ***	4.01 *
	-3.93	-3.19	-5.57	-0.53		0.42	4.25	
% Age 15-24	-1.28 *	-1.12 *	-2.82 ***	-0.38	5.63 *	-2.69	0.76	7.28 **
	-2.33	-2.16	-3.54	-0.58		-2.56 **	1.02	
% Age 25-34	-0.82	-0.49	-2.24 **	0.32	5.13 *	-0.44	2.41 **	3.80 *
	-1.36	-0.86	-2.62	0.43		-0.35	3.04	
% Age 35-54	0.16	-0.25	-1.63	0.10	1.93	-5.68 ***	-1.51	7.45 **
	0.25	-0.41	-1.59	0.14		-4.45	-1.80	
% Age 55-64	-1.63 *	-1.22	-2.88 **	-0.27	4.49 *	-1.29	0.63	1.32
	-2.40	-1.92	-3.02	-0.35		-0.96	0.65	
% Age 65-74	-2.75 **	-2.55 **	-4.97 **	-1.38	3.62	-4.30 *	2.30	8.01 **
	-2.66	-2.61	-3.62	-1.06		-2.32	1.60	
Urban Indicator	2.86	1.33	0.56	3.15	0.89	5.84 *	1.11	1.53
	1.81	0.96	0.27	1.74		1.95	0.46	
Annual Rainfall	0.05 *	0.03	0.03	-0.06	0.05	0.07	0.01	0.88
	2.44	1.45	0.91	-1.49		1.86	0.31	
Mean Temp.	3.90 ***	2.79 *	1.18	0.65	3.02	2.45	0.55	0.42
	3.35	2.51	0.60	0.46		1.00	0.34	
* < 0.05	** < 0.01	***< 0.001						
Spatial Lag of Y		0.11 **	0.07			0.41 ***		
		2.82	1.74			6.47		
N	840	840	379	461		379	461	
R^2/Pseudo R^2	0.77	0.74	0.76			0.63		
Spatial Chow Test			36.31 ***			18.31		

(1) beta, (2) t-valiue (OLS) or z-value (spatial 2SLS): Same for all variables

Table 2. cont.

	West-Rest						West-Southeast-North			
	Robust Spatial Lag (2SLS/IV)									
	DV: SMRs Male			DV: SMRs Female			DV: SMRs Total			
	Model 5			Model 6			Model 7			
	West	Rest	Spatial Chow	West	Rest	Spatial Chov	West	Southeast	North	Sp. Chov
Intercept (1)	176.65	36.79	1.12	345.63 **	1.02	6.59 **	245.06 *	83.52	22.41	2.50
(2)	1.59	0.52		3.13	0.01		2.37	1.10	0.21	
Deprivation										
Low	-7.10 *	-5.19 *	0.24	-2.86	-4.74 *	0.21	-5.73 *	-4.15	-7.31 **	0.73
	-2.21	-2.35		-0.86	-1.99		-2.03	-1.60	-2.73	
High	31.00 *	25.08 ***	1.43	23.62 ***	16.50 ***	1.80	27.22 ***	21.11 ***	21.03 ***	2.20
	7.95	7.84		5.72	4.78		8.33	6.32	4.69	
% Male							0.51	-2.79 **	-0.65	3.97
							0.36	-2.71	-0.46	
% Age 0-4	2.79	-0.02	0.72	-1.75	1.14	0.66	0.52	-0.55	0.22	0.11
	0.99	-0.01		-0.60	0.57		0.22	-0.24	0.10	
% Age 5-14	-0.28	2.75 **	2.83	1.30	3.27 **	1.08	0.55	4.52 ***	2.46	5.67
	-0.18	2.91		0.85	2.90		0.42	4.35	1.79	
% Age 15-24	-1.35	0.10	1.00	-3.93 ***	0.24	9.70 **	-2.63 **	0.65	0.84	7.14
	-1.10	0.13		-3.69	0.29		-2.51	0.69	0.78	
% Age 25-34	-0.57	1.68 *	2.19	-0.10	2.04 **	1.42	-0.33	3.01 ***	1.97	4.99
	-0.44	2.09		-0.06	2.47		-0.27	3.48	1.47	
% Age 35-54	-4.46 ***	-1.81 *	2.58	-6.13 ***	-2.17 *	5.21 *	-5.61 ***	-1.17	-1.94	7.15
	-3.18	-2.10		-4.26	-2.25		-4.40	-0.94	-1.69	
% Age 55-64	-1.23	-1.18	0.00	-1.23	2.00 *	2.95	-1.35	1.91	1.07	3.32
	-0.87	-1.18		-0.78	1.95		-1.00	1.57	0.80	
% Age 65-74	-2.75	2.14	3.29	-5.65 **	1.11	6.09 **	-4.13 *	1.45	1.33	5.77
	-1.26	1.34		-2.67	0.62		-2.23	0.79	0.62	
Urban Indicatc	5.59	0.87	1.35	4.26	3.44	0.04	5.93 *	1.10	-1.50	2.38
	1.71	0.35		1.28	1.37		1.98	0.37	-0.34	
Annual Rainfal	0.09 *	0.02	1.20	0.03	-0.01	0.24	0.07	0.03	0.03	0.47
	2.24	0.39		0.54	-0.15		1.88	0.44	0.65	
Mean Temp.	5.51 *	-0.11	2.86	-1.56	0.27	0.23	2.52	-0.26	3.51	1.69
	1.95	-0.06		-0.51	0.12		1.03	-0.12	1.66	
* < 0.05	** < 0.01	***< 0.001								
Spatial Lag of	0.41 ***			0.43 ***			0.38 ***			
	6.09			5.34			6.39			
N	379	461		379	461		379	229	232	
R^2/Pseudo R^2	0.60			0.50			0.64			
Spatial Chow	16.49			16.46			52.36 **			

(1) beta, (2) t-valiue (OLS) or z-value (spatial 2SLS): Same for all variables